### → Abyan Ardiatama

24060120140161

Praktikum 4 ML

### **Hierarchial Clustering**

```
import numpy as np
import pandas as pd
from scipy import ndimage
from scipy.cluster import hierarchy
from scipy.spatial import distance_matrix
from matplotlib import pyplot as plt
from sklearn import manifold,datasets
from sklearn.cluster import AgglomerativeClustering
from sklearn.datasets import make_blobs
%matplotlib inline
```

```
df = pd.read_csv('cars_clus.csv')
```

9

70.9

#### print(df.head(10))

		manufa	ict	model	Sã	ales	resa	le	typ	oe .	pric	ce	engine_s	horsepow	wheelbas
(	0	Acu	ıra I	ntegra	16	919	16.	36		0	21.	. 5	1.8	140	101.2
	1	Acu	ıra	TL	39	384	19.8	75		0	28.	4	3.2	225	108.1
	2	Acu	ıra	CL	14	.114	18.2	25		0	\$null	L\$	3.2	225	106.9
	3	Acu	ıra	RL	8	588	29.7	25		0	4	12	3.5	210	114.6
	4	Αu	ıdi	A4	20	397	22.2	55		0	23.9	99	1.8	150	102.6
	5	Αu	ıdi	A6	18	3.78	23.5	55		0	33.9	95	2.8	200	108.7
(	6	Αu	ıdi	A8		1.38		39		0	6	52	4.2	310	113
	7	В	BMW	323i	19	.747	\$nul	.1\$		0	26.9	99	2.5	170	107.3
	8	В	BMW	328i	9	231	28.6	75		0	33.	4	2.8	193	107.3
(	9 BMW		BMW	528i	17.527		36.1	36.125		0	38.9		2.8	193	111.4
				h curb	_wgt	fue		n		ln	sales	р	artition		
(	0	67.3			<b>.</b> 639		13.2		28		2.828		0		
	1	70.3	192.	9 3	.517		17.2		25		3.673		0		
	2	70.6	19	2	3.47		17.2		26		2.647		0		
	3	71.4	196.	6	3.85		18		22		2.15		0		
4	4	68.2	17	8 2	. 998		16.4		27		3.015		0		
	5			561 18		18.5		22		2.933		0			
(	6 74 198.		2 3			23.7		21		0.322		0			
	7	68.4	17	6 3	. 179		16.6	26	5.1		2.983		0		
	8	68.5	17	6 3	. 197		16.6		24		2.223		0		

print("Shape of dataset:", df.shape)
# Check if there is any missing value
df.isnull().sum()

188

3.472

18.5

24.8

2.864

```
Shape of dataset: (159, 16)
manufact
model
              0
sales
              0
resale
              0
              0
type
price
              0
engine_s
              0
horsepow
              0
wheelbas
              0
width
              0
length
              0
curb_wgt
              0
fuel_cap
              0
mpg
lnsales
              0
partition
dtype: int64
```

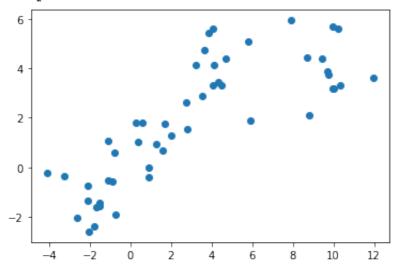
```
# Data Cleaning, convert to numerical, if can't drop the data
df[['sales','resale','type','price','engine_s','horsepow','wheelbas','width','le
df = df.dropna()
df = df.reset index(drop=True)
print("Shape of dataset after cleaning: ", df.shape)
# Check if there is any missing value
df.isnull().sum()
    Shape of dataset after cleaning: (117, 16)
    manufact
    model
    sales
     resale
    type
                  0
    price
    engine_s
    horsepow
    wheelbas
                  0
    width
                  0
    length
    curb_wgt
    fuel_cap
    mpg
     lnsales
                  0
    partition
    dtype: int64
```

## ▼ Tugas 1

Agglomerative Clustering Single Linkage dan Average Linkage Dataset cars\_clustering

X1,y1=make\_blobs(n\_samples=50,centers=[[4,4],[-2,-1],[1,1],[10,4]], cluster\_std=plt.scatter(X1[:,0],X1[:,1], marker='o')

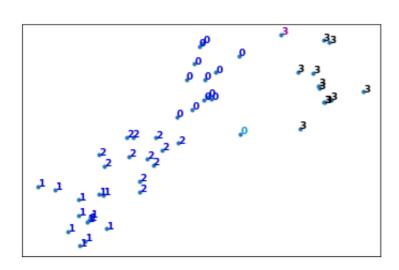
<matplotlib.collections.PathCollection at 0x7f13a670d5d0>



agglom=AgglomerativeClustering(n\_clusters=4,linkage='single')
agglom.fit(X1,y1)

AgglomerativeClustering(linkage='single', n\_clusters=4)

```
#Create Figure of size 6 inches and 4 inches
plt.figure(figsize=(6,4))
#These 2 lines of code are used to scale the data points down
#or else the data points will be scattered very far apart
#Create amnimum and maximum range of X1
x_min,x_max=np.min(X1,axis=0), np.max(X1,axis=0)
#get the average distance for X1
X1 = (X1-x_min) / (x_max -x_min)
#This loop displays all of the datapoints
for i in range(X1.shape[0]):
  #Replace the data points with their respective cluster value
  #(ex.0) and is color coded with a colormap (plt.cm.spectral)
  plt.text(X1[i, 0], X1[i, 1], str(y1[i]),
           color=plt.cm.nipy_spectral(agglom.labels_[i] / 10.),
           fontdict={'weight':'bold','size':9})
#Remove the x ticks, y ticks, x and y axis
plt.xticks([])
plt.yticks([])
#plt.axis('off')
#Display the plot of the original data before clustering
plt.scatter(X1[:, 0], X1[:, 1], marker='.')
#Display the plot
plt.show()
```



```
#Plotting the dendorgram
dist_matrix = distance_matrix(X1,X1)
print(dist_matrix)
```

#Use linkage class from the hierarchy

Z = hierarchy.linkage(dist\_matrix,'complete')

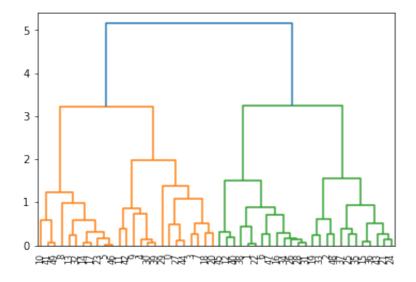
X = hierarchy.linkage(dist\_matrix,'single')

Y = hierarchy.linkage(dist\_matrix, 'average')

/usr/local/lib/python3.7/dist-packages/ipykernel\_launcher.py:2: ClusterWarn

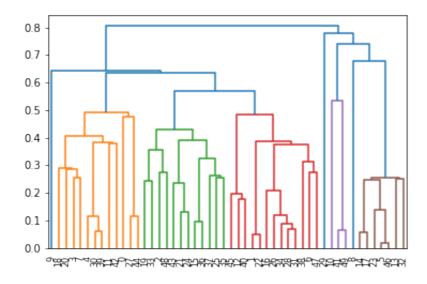
/usr/local/lib/python3.7/dist-packages/ipykernel\_launcher.py:3: ClusterWarn This is separate from the ipykernel package so we can avoid doing imports /usr/local/lib/python3.7/dist-packages/ipykernel\_launcher.py:4: ClusterWarn after removing the cwd from sys.path.

#### dendro·=·hierarchy.dendrogram(Z)

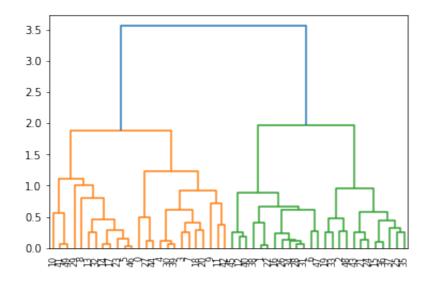


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#### dendro = hierarchy.dendrogram(X)



#### dendro = hierarchy.dendrogram(Y)



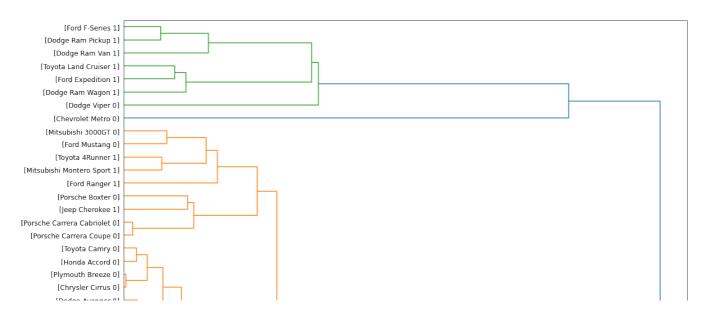
# ▼ Tugas 2

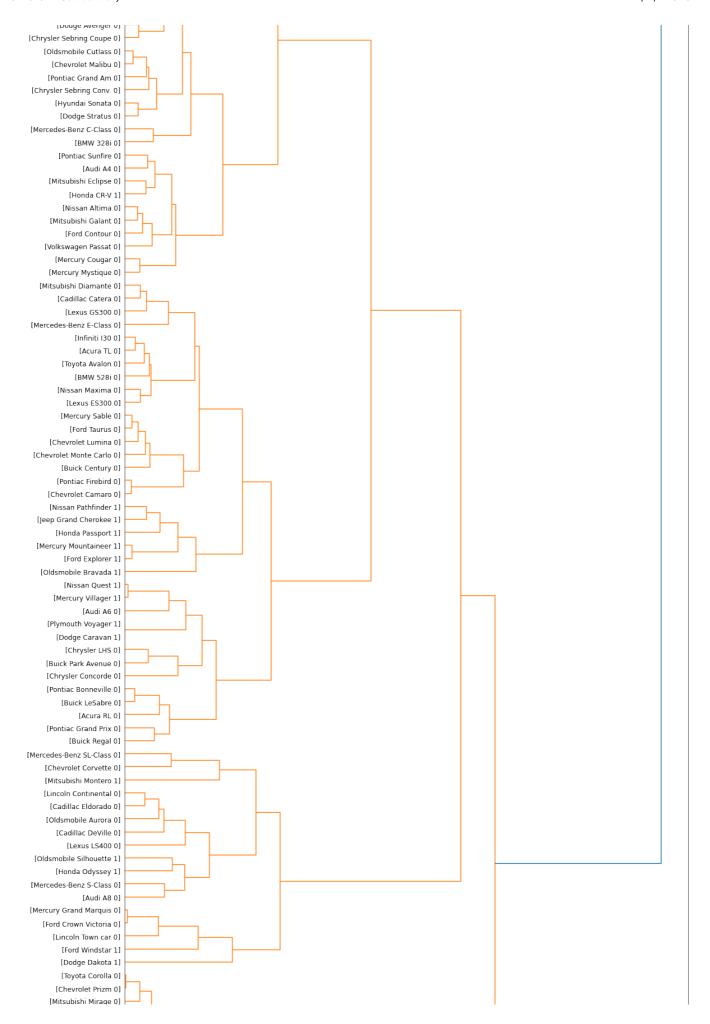
Agglomerative Clustering menggunakan scipy dan scikit-learn Single Linkage dan Average Linkage Dataset cars\_clustering

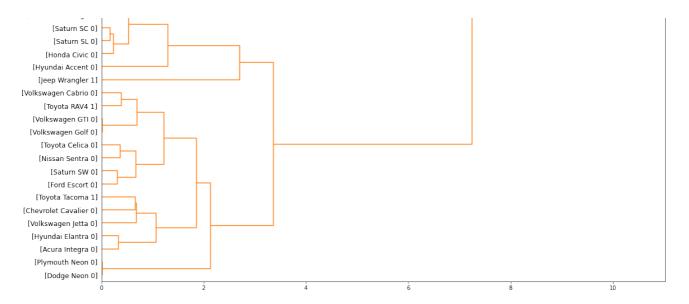
```
# Feature selection
featureset = df[['engine_s', 'horsepow', 'wheelbas', 'width', 'length', 'curb_wg']
featureset.head()
#Normalization
from sklearn.preprocessing import MinMaxScaler
x = featureset.values #return numpy array
min max scaler = MinMaxScaler()
feature_mtx = min_max_scaler.fit_transform(x)
feature mtx [0:5]
    array([[0.11428571, 0.21518987, 0.18655098, 0.28143713, 0.30625832,
             0.2310559 , 0.13364055, 0.43333333],
            [0.31428571, 0.43037975, 0.3362256 , 0.46107784, 0.5792277 ,
            0.50372671, 0.31797235, 0.33333333],
            [0.35714286, 0.39240506, 0.47722343, 0.52694611, 0.62849534,
             0.60714286, 0.35483871, 0.23333333],
            [0.11428571, 0.24050633, 0.21691974, 0.33532934, 0.38082557,
            0.34254658, 0.28110599, 0.4
                                               ],
            [0.25714286, 0.36708861, 0.34924078, 0.80838323, 0.56724368,
            0.5173913 , 0.37788018, 0.23333333]])
#Clustering with scipy
import scipy
leng = feature mtx.shape[0]
D = scipy.zeros([leng,leng])
for i in range(leng):
  for j in range(leng):
    D[i,j] = scipy.spatial.distance.euclidean(feature_mtx[i],feature_mtx[j])
    /usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:4: Deprecation
      after removing the cwd from sys.path.
#Single Linkage, Average Linkage, and Complete Linkage
import pylab
import scipy.cluster.hierarchy
Z = hierarchy.linkage(D, 'complete')
X = hierarchy.linkage(D, 'single')
Y = hierarchy.linkage(D, 'average')
    /usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:4: ClusterWarn
      after removing the cwd from sys.path.
    /usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:5: ClusterWarn
    /usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:6: ClusterWarn
```

```
from scipy.cluster.hierarchy import fcluster
max d = 3
clusters = fcluster(Z,max_d,criterion='distance')
     array([ 1,
                                   4,
                                                             5,
                      5,
                               5,
                                            5,
                                                5,
                                                    5,
                                                         5,
                  5,
                          6,
                                       6,
                                                                 4,
                                                                          5,
                                                                                   6,
             5,
                  5,
                      5,
                          4,
                               2, 11,
                                       6,
                                            6,
                                                5,
                                                    6,
                                                         5,
                                                             1,
                                                                 6,
                                                                      6, 10,
                                                                              9,
                                                                                   8,
             9,
                  3,
                                       5,
                                                         8,
                                                                      2,
                                            3,
                                                5,
                                                                          6,
                      5,
                          1,
                               7,
                                   6,
                                                    3,
                                                             7,
                                                                 9,
                                                                              6,
                  2,
                          6,
                                   2,
                                                5,
             4.
                               5,
                                            5,
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                                                                 3,
                                                                      2,
                      1,
                                                    5,
                                                                          6,
                     7,
                                                5,
                                                         5,
             7,
                                                                      1,
                                                                                   5,
                  4,
                          6,
                               6,
                                   5,
                                       3,
                                           5,
                                                    6,
                                                                 4,
                                                                          6,
                          5,
                                            5,
                                                         5,
             5,
                  6,
                      4,
                               4,
                                   1,
                                       6,
                                                6,
                                                    6,
                                                                 5,
                                                                      7,
                                                                          7,
                                                                                   2,
             2,
                  1,
                      2,
                               5,
                                   1,
                                                7,
                                                         1,
                                                             1,
                                                                          1],
                          6,
                                       1,
                                            1,
                                                    8,
                                                                 6,
                                                                      1.
           dtype=int32)
from scipy.cluster.hierarchy import fcluster
clusters = fcluster(Z, k, criterion='maxclust')
clusters
     array([1, 3, 3, 3, 3, 2, 3, 3, 3, 3, 3, 2, 2, 3, 1, 3, 3, 3, 3, 2, 1,
            5, 3, 3, 3, 3, 1, 3, 3, 4, 4, 4, 4, 2, 3, 1, 3, 3, 3, 2, 3, 2,
            4, 3, 4, 1, 3, 3, 3, 2, 1, 1, 3, 3, 1, 3, 3, 3, 3, 2, 2, 2, 1, 3,
            3, 3, 3, 2, 3, 3, 3, 3, 2, 3, 3, 3, 2, 2, 1, 3, 3, 3, 3, 3, 2,
            3, 2, 1, 3, 3, 3, 3, 3, 3, 3, 3, 3, 1, 1, 1, 1, 3, 3, 1, 1, 1,
            3, 4, 1, 1, 3, 1, 1], dtype=int32)
#Plotting Dendrogram
fig = pylab figure(figsize = (18,50))
def llf(id):
  return '[%s %s %s]' % (df['manufact'][id],df['model'][id], int(float(df['type
#Plotting Complete Linkage
```

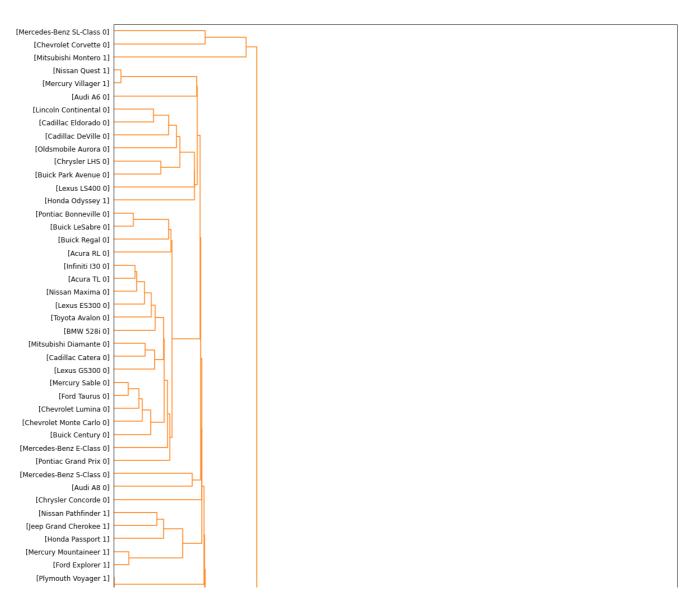
dendro = hierarchy.dendrogram(Z, leaf label func=llf, leaf rotation=0, leaf for

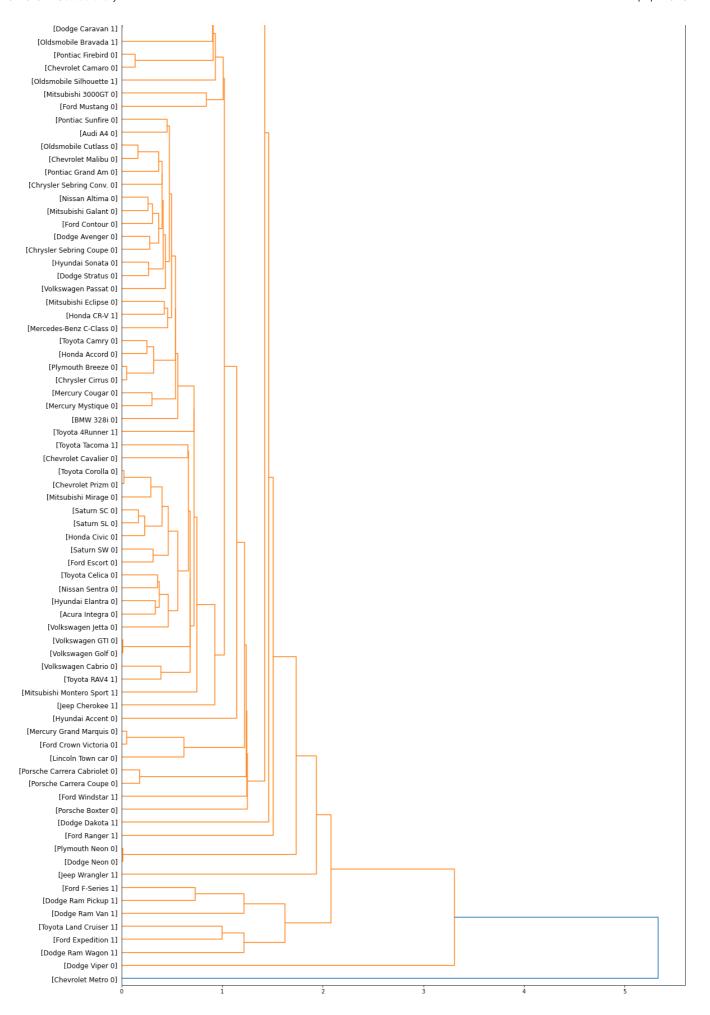




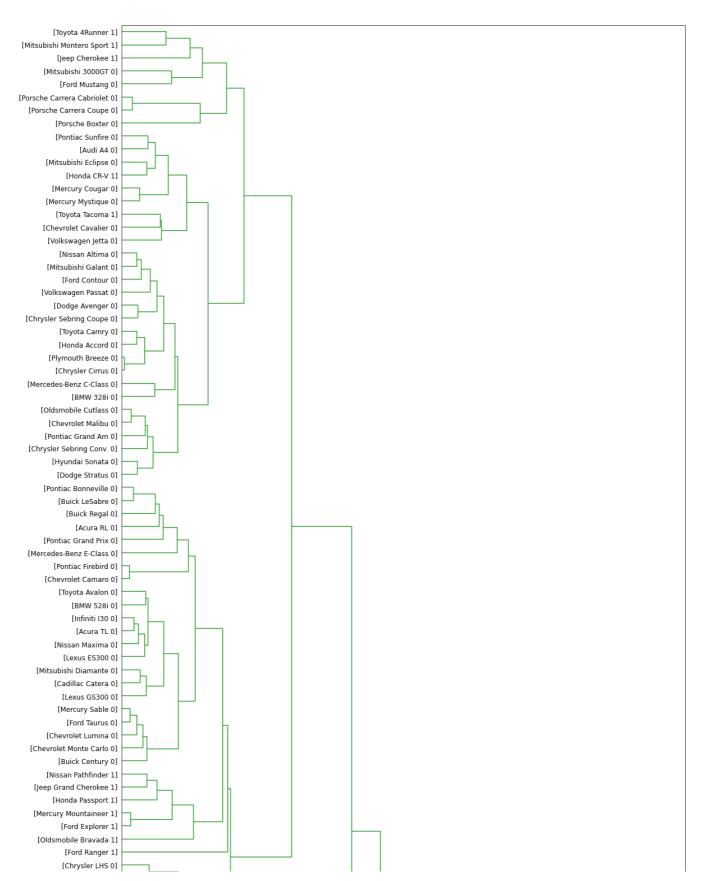


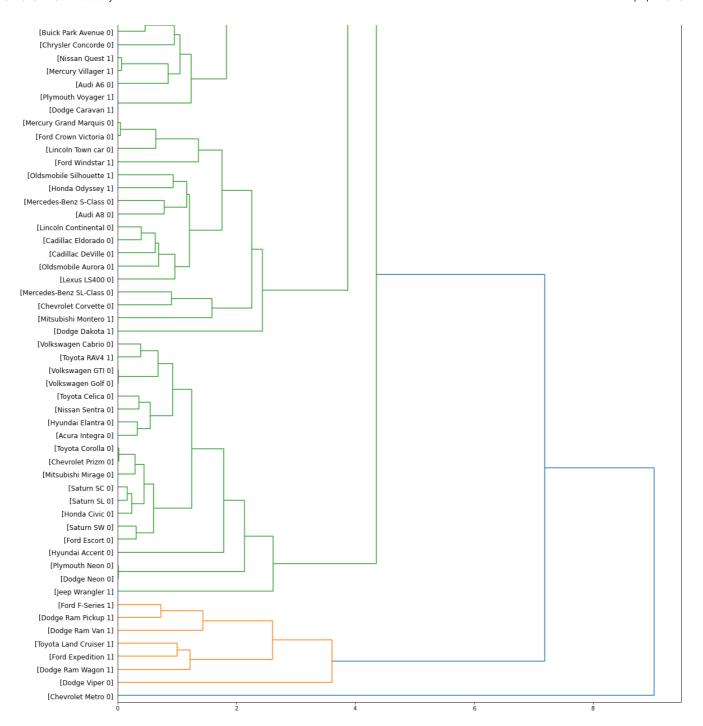
#Plotting Single Linkage
fig = pylab.figure(figsize=(18,50))
dendro = hierarchy.dendrogram(X, leaf\_label\_func=llf, leaf\_rotation=0, leaf\_font





#Plotting · Average · Linkage
fig · = · pylab · figure(figsize=(18,50))
dendro · = · hierarchy · dendrogram(Y, · leaf\_label\_func=llf, · leaf\_rotation=0, · leaf\_for





## ▼ Tugas 3

Agglomerative Cluster menggunakan scikit-learn dan scipy dengan single linkage, average linkage, dan complete linkage menggunakan dataset iris

```
# Import iris dataset
from sklearn.datasets import load_iris
iris = load_iris()
```

# Convert to df
df = pd.DataFrame(iris.data, columns=iris.feature\_names)
df['target'] = iris.target

df.head()

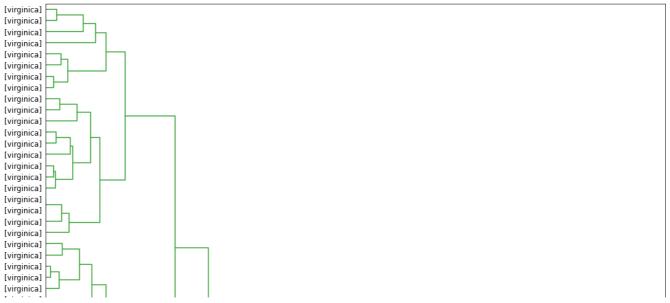
	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
0	5.1	3.5	1.4	0.2	0
1	4.9	3.0	1.4	0.2	0
2	4.7	3.2	1.3	0.2	0
3	4.6	3.1	1.5	0.2	0
4	5.0	3.6	1.4	0.2	0

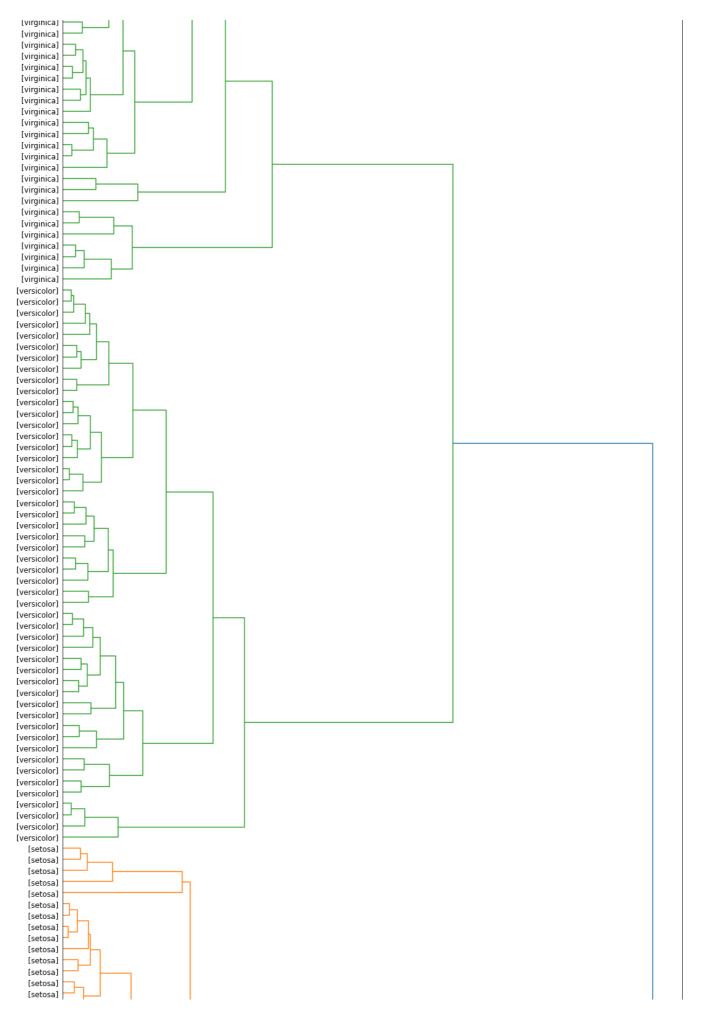
```
#Normalization
```

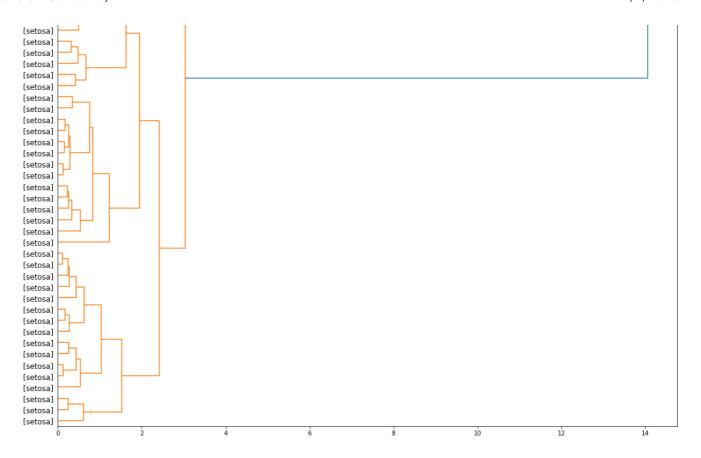
```
from sklearn.preprocessing import MinMaxScaler
x = df.values
min_max_scaler = MinMaxScaler()
feature_mtx = min_max_scaler.fit_transform(x)
feature_mtx [0:5]
```

```
array([[0.22222222, 0.625 , 0.06779661, 0.04166667, 0. ], [0.16666667, 0.41666667, 0.06779661, 0.04166667, 0. ], [0.11111111, 0.5 , 0.05084746, 0.04166667, 0. ], [0.08333333, 0.45833333, 0.08474576, 0.04166667, 0. ], [0.19444444, 0.666666667, 0.06779661, 0.04166667, 0. ]])
```

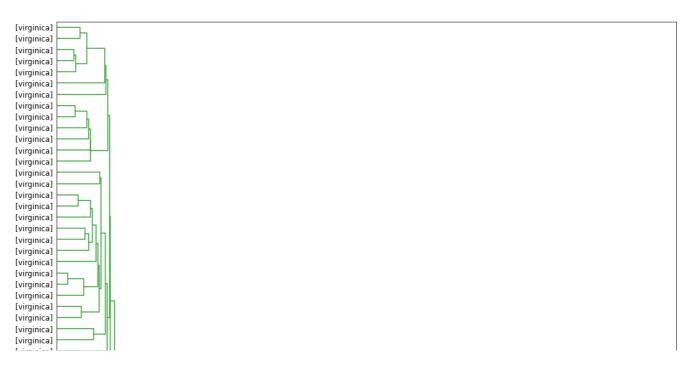
```
#Clustering with scipy
import scipy
leng = feature_mtx.shape[0]
D = scipy.zeros([leng,leng])
for i in range(leng):
  for j in range(leng):
    D[i,j] = scipy.spatial.distance.euclidean(feature_mtx[i],feature_mtx[j])
    /usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:4: Deprecation
       after removing the cwd from sys.path.
#Single Linkage, Average Linkage, and Complete Linkage
import pylab
import scipy.cluster.hierarchy
Z = hierarchy.linkage(D, 'complete')
X = hierarchy.linkage(D, 'single')
Y = hierarchy.linkage(D, 'average')
    /usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:4: ClusterWarn
       after removing the cwd from sys.path.
     /usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:5: ClusterWarn
    /usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:6: ClusterWarn
def llf(id):
    return '[%s]' % ( iris.target_names[df['target'][id]] )
#Plotting · Complete · Linkage
fig = pylab.figure(figsize = (18,50))
dendro·-·hierarchy.dendrogram(Z,·leaf label func=llf,·leaf rotation=0,·leaf for
```

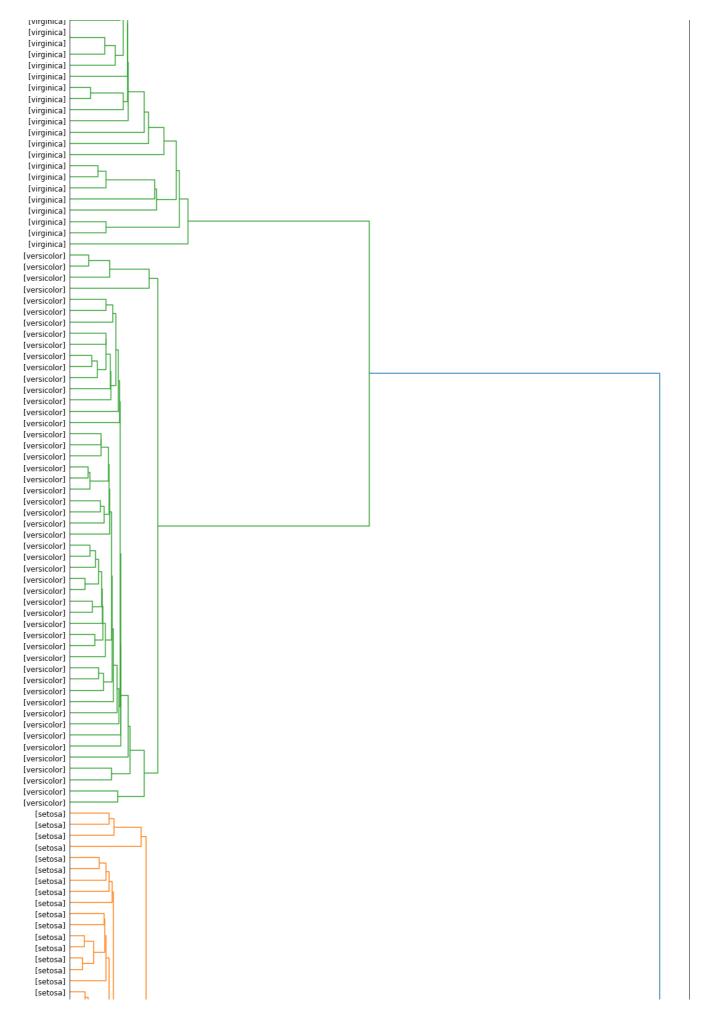


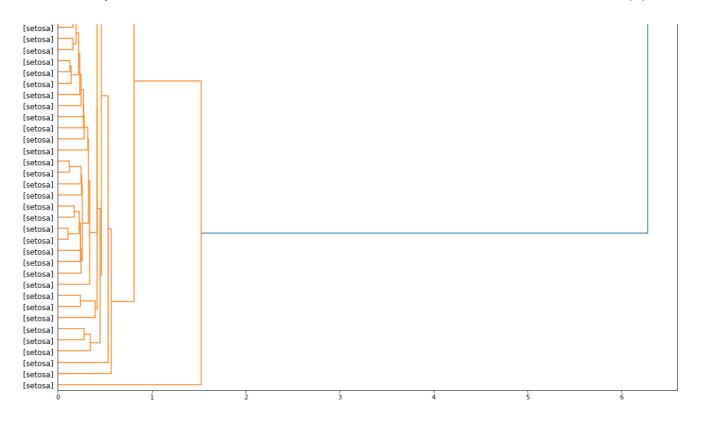




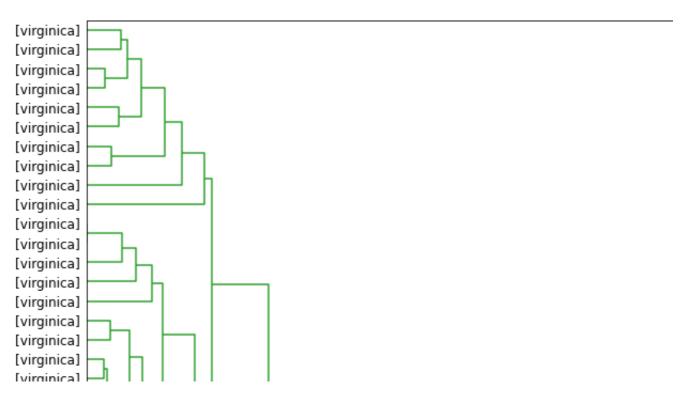
#Plotting Single Linkage
fig = pylab.figure(figsize=(18,50))
dendro = hierarchy.dendrogram(X, leaf\_label\_func=llf, leaf\_rotation=0, leaf\_font

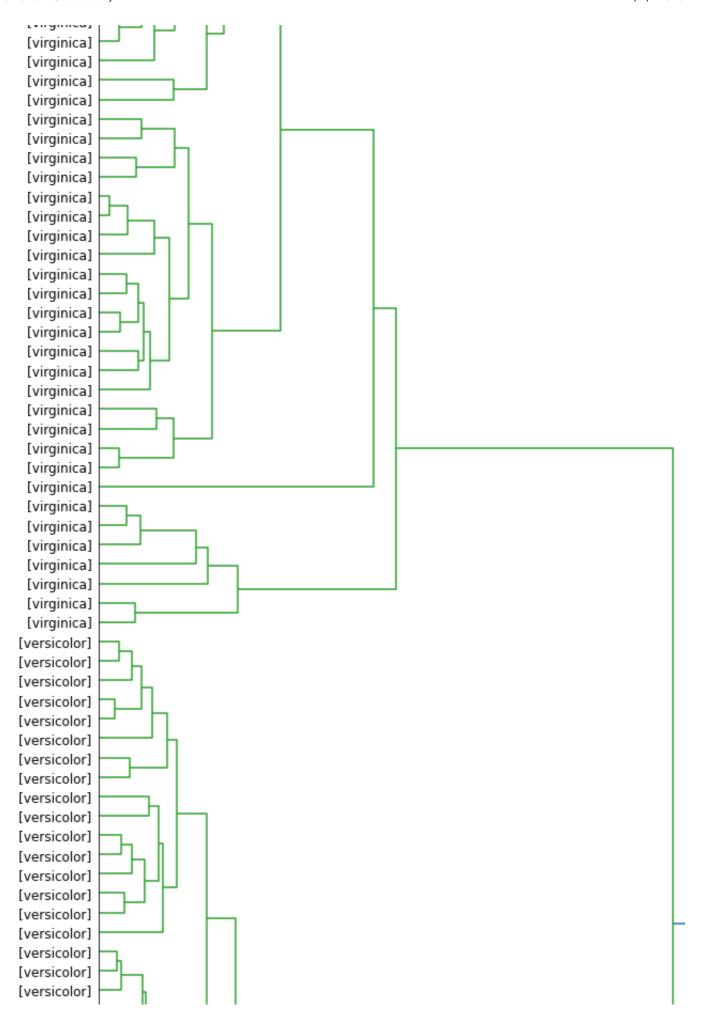


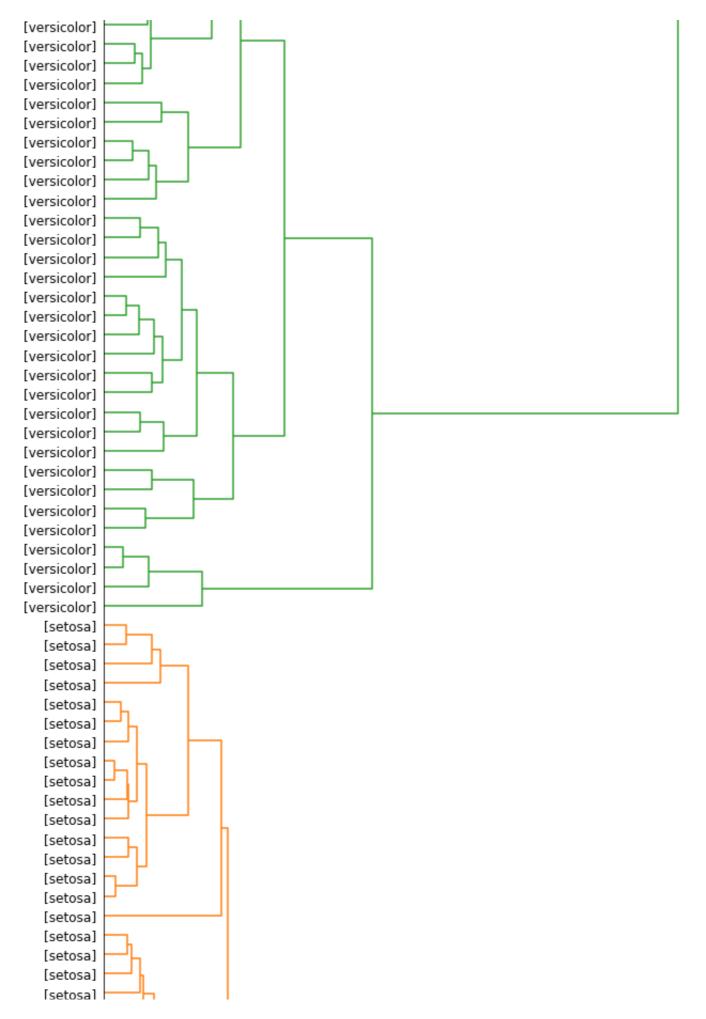


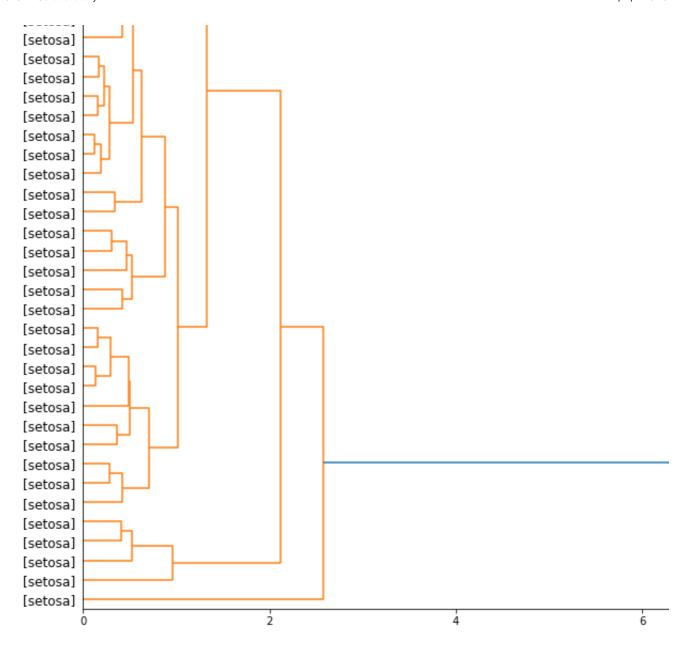


#Plotting Average Linkage
fig = pylab.figure(figsize=(18,50))
dendro = hierarchy.dendrogram(Y, leaf\_label\_func=llf, leaf\_rotation=0, leaf\_for









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